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ABSTRACT

There are currently three main approaches to parameter estimation in item response theory (IRT): (1) joint maximum likelihood, exemplified by LOGIST, yielding maximum likelihood estimates; (2) marginal maximum likelihood, exemplified by BILOG, yielding maximum likelihood estimates of item parameters (ability parameters can be estimated subsequently, using Bayesian procedures); and (3) Bayesian approaches--parameter estimates are usually the mode or mean of the posterior distribution of the parameter estimated. Advantages and disadvantages of these three methods are discussed and compared. (Author/BW)

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MAXIMUM LIKELIHOOD AND BAYESIAN PARAMETER ESTIMATION IN ITEM RESPONSE THEORY

Frederic M. Lord

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Frederic M. Lord, Principal Investigator

Educational Testing Service

Princeton, New Jersey

August 1984

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Maximum Likelihood and Bayesian Parameter Estimation in Item Response Theory

Frederic M. Lord

Abstract

Advantages and disadvantages of joint maximum likelihood, marginal maximum likelihood, and Bayesian methods of parameter estimation in item response theory are discussed and compared.

Maximum Likelihood and Bayesian Parameter Estimation in Item Response Theory*

There are currently three main approaches to parameter estimation in item response theory (IRT):

1. Joint maximum likelihood, exemplified by LOGIST, yielding maximum likelihood estimates (Wingersky, 1983).
2. Marginal maximum likelihood, exemplified by BILOG. This approach currently yields maximum likelihood estimates of <u>item parameters</u>. Ability parameters can be estimated subsequently, using Bayesian procedures (Mislevy & Bock, 1981).
3. Bayesian approaches: parameter estimates are usually the mode (or mean) of the posterior distribution of the parameter estimated (Swaminathan & Gifford, in press).

The quantity maximized by each approach is shown below for a test of n items administered to N examinees. $P_i(\theta_a)$ is the probability of success on item i for examinee a at ability level θ_a, $Q_i(\theta_a) = 1 - P_i(\theta_a)$, u_{ia} is the response of examinee a to item i, assumed here to be either 0 or 1, and $g(\ )$ denotes a prior distribution of parameters.

Joint maximum likelihood:

$$\text{Maximize } L(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) = \prod_{a=1}^{N} \prod_{i=1}^{n} [P_i(\theta_a)]^{u_{ia}} [Q_i(\theta_a)]^{1-u_{ia}} \tag{1}$$

$$\text{or } \log L(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) = \sum_{a=1}^{N} \sum_{i=1}^{n} [u_{ia} \log P_i(\theta_a) + (1 - u_{ia}) \log Q_i(\theta_a)] \quad .$$

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Marginal maximum likelihood of <u>item parameters</u>:

$$\text{Maximize} \quad L(\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) = \prod_{a=1}^{N} \int_{-\infty}^{\infty} g(\theta_a)\, L(\theta_a;\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c})\, d\theta_a \quad . \tag{2}$$

Bayesian modal estimation:

$$\text{Maximize} \quad f(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) = L(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c})\,g_1(\underset{\sim}{\theta})\,g_2(\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) \tag{3}$$

$$\text{or} \quad \log f(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) = \log L(\underset{\sim}{\theta};\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) + \log g_1(\underset{\sim}{\theta}) + \log g_2(\underset{\sim}{a},\underset{\sim}{b},\underset{\sim}{c}) \quad .$$

LOGIST finds the ability and item parameter values that maximize the likelihood function of the observations. Bayesian methods typically multiply this likelihood by a prior for each of the parameters, obtaining the joint posterior distribution of the parameters, which are usually assumed to be independently distributed. The Bayesian modal estimates (BME) of all the parameters are the values at the mode of this joint posterior distribution. Marginal maximum likelihood multiplies the original likelihood by a prior on ability, eliminates the ability parameters by integration, and obtains maximum likelihood estimates of the item parameters by maximizing the resulting 'marginal' likelihood function. Supplementary Bayesian procedures may be used to obtain ability parameter estimates. Bayesian priors on item parameters may also be used in MMLE.

When approximately parallel test forms are administered year after year to similar populations of examinees, it becomes possible to deduce appropriate prior distributions for the item and the ability parameters from past results. In such a situation, Bayesian procedures should certainly yield better parameter estimates than maximum likelihood, since Bayesian procedures make use of more information. Even in the absence of data from previous administrations, Bock's BILOG is able to work with a reasonable prior distribution of ability generated directly just from the current data.

Marginal maximum likelihood has an important advantage over joint maximum likelihood, since it can estimate item parameters without having to estimate ability parameters. The advantage is not one of computational speed but rather of theoretical accuracy. When there are one or two thousand examinees and 40 or more items per person, there will be a little difference between the estimates. In cases where there are only 10 or 15 items per person, joint maximum likelihood will obtain biased estimates of ability parameters, especially at low ability levels. This then causes the item parameters to be misestimated, even though the number of examinees per item is large.

Let us turn now to Bayesian procedures. From the mathematical statistician's point of view, one clear virtue of Bayesian methods is that if the posterior <u>mean</u> is used as a parameter estimate, this estimator minimizes the overall mean squared error of estimation, provided the appropriate prior distribution is used. In the case of ability parameters, for example, the quantity minimized is

$$MSE = \mathcal{E}(\hat{\theta}_a - \theta_a)^2 \quad , \tag{4}$$

where $\hat{\theta}$ is an estimate of θ and $\mathcal{E}$ denotes expectation over all examinees. The posterior mean achieves this important result by accepting increased estimation bias in return for reduced MSE. The BME does not minimize this MSE unless the mode of the posterior distribution coincides with its mean, which is not the case in IRT estimation problems. Nevertheless, the BME may be close to the posterior mean.

Why does the posterior mean do better than the maximum likelihood estimate (MLE) in minimizing MSE? When item parameters are known, the MLE of ability assigned to a given response pattern must always be the same. In Bayesian methods, however, the ability estimate assigned to a given response pattern depends on the characteristics of the entire group analyzed. It is this additional flexibility that allows Bayesian methods to obtain a smaller MSE.

Figure 1 shows the bias, estimated by asymptotic formula (7) accurate through terms of order $1/n$, for the BME of θ (dashed curve) based on a normal prior and for the MLE of θ (solid curve), calculated for an 90-item SAT Verbal test that first came to hand, using the three-parameter logistic model. The values shown in the figure assume the item parameters to be known.

The MLE and the BME are biased in opposite directions. The BME is more biased than the MLE. Note that neither bias is linearly related to θ; consequently, the bias cannot be corrected by a simple linear transformation of the estimates.

When a normal prior is used for θ, the asymptotic standard error of the BME and of the MLE for estimated θ are identical to the usual order of approximation ($1/n$). The (familiar) formula for both asymptotic standard

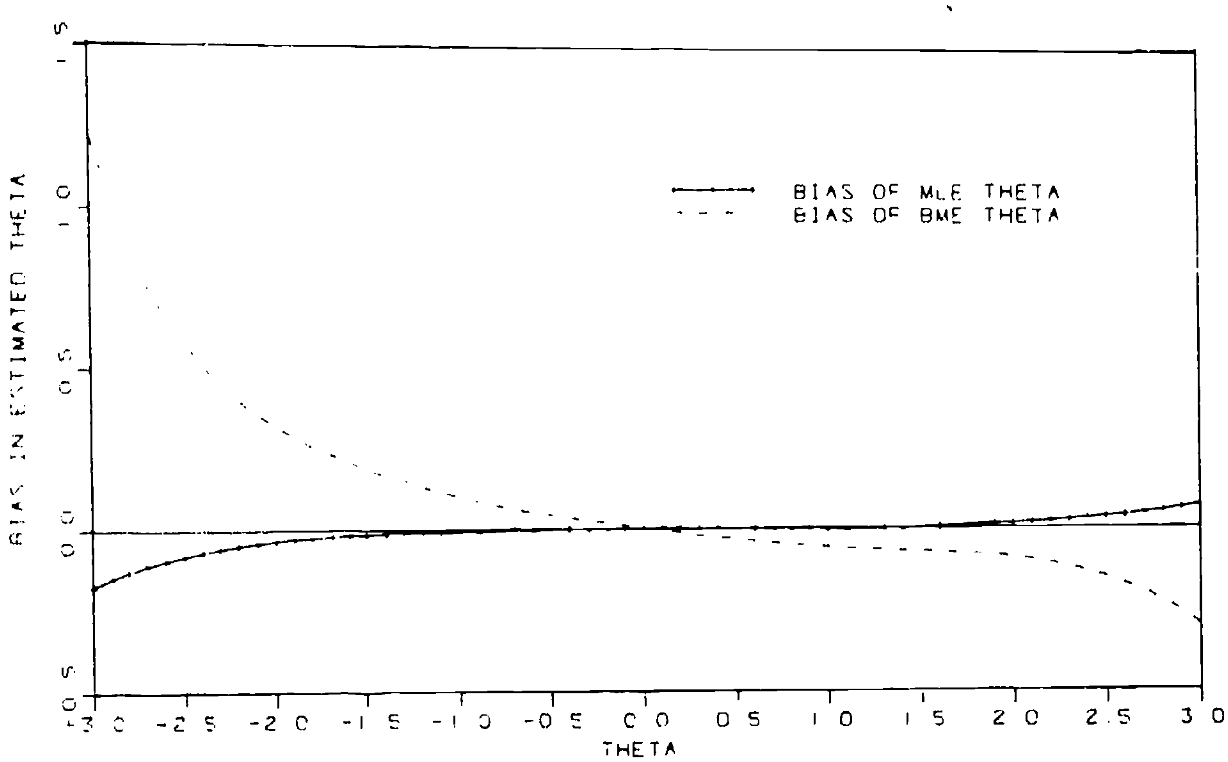

Figure 1. Bias in estimated ability for an 90-item SAT Verbal test.

errors is

$$S.E.(\hat{\theta}) \doteq \left(\sum_{i=1}^{n} \frac{P_i'^2}{P_i Q_i} \right)^{-1/2} , \qquad (5)$$

the square root of the reciprocal of the test information function (I). This is also the asymptotic formula for both MSE's. If the S.E. were written out including higher order terms, the Bayesian S.E. would be smaller than the maximum likelihood S.E. by an amount of order $1/n^2$.

The asymptotic bias in the MLE in the three-parameter logistic model is (Lord, 1983)

$$\text{Bias}(\text{MLE}(\theta)) \doteq \frac{D}{I^2} \sum_{i=1}^{n} a_i I_i (\phi_i - \frac{1}{2}) \qquad (6)$$

where $D = 1.7$, $I_i \equiv \frac{P_i'^2}{P_i Q_i}$, $P_i' \equiv \frac{\partial P_i}{\partial \theta}$, $\phi_i \equiv \frac{P_i - c_i}{1 - c_i}$,

and a_i and c_i are the discrimination parameter and lower asymptote for item i . The asymptotic bias for the BME is found by the same method to be

$$\text{Bias}(\text{BME}(\theta)) \doteq \text{Bias}(\text{MLE}(\theta)) - \frac{\theta}{I} . \qquad (7)$$

Both (6) and (7) are of order $1/n$.

Because of the bias in the BME, which is best described as regression towards the mean, the variance of the BME across examinees is less than the

variance of the true θ values. Many people apply a linear transformation to the BME's in an attempt to make the variance (across examinees) of the resulting transformed estimates equal to the variance of the true θ values. This procedure is only a rough approximation, since it is based on an assumption of linear regression of BME on θ, whereas the true regression is curvilinear. From the mathematical statistician's point of view, a linearly transformed BME or posterior mean, or a curvilinearly transformed BME or posterior mean, are nonstandard types of estimators. Such transformed estimators no longer have the property of minimizing MSE.

A further problem arises: Minimizing MSE on the θ scale is not the same as minimizing MSE on the true-score scale, or on some other transformed ability scale. Bayesian estimates of ability will differ in a substantive way depending on the scale chosen for measuring ability. This problem does not arise in maximum likelihood estimation.

Although minimizing MSE on the θ scale seems appropriate to many people, the writer believes it is inappropriate. Large differences in θ's at the extremes of the ability scale are of very much less importance for most practical purposes than smaller differences in the middle of the scale. If the extremes of the scale were important to us, we would be putting more easy items or more hard items in our tests. An average of squared differences, averaged over all parts of the scale, is thus not of real interest. A procedure that attempts to minimize such an average will devote most effort to minimizing the large squared differences found at the extremes of the scale, thus partially neglecting more important differences near the middle of the scale.

In the case of item-parameter estimation, the idea of minimizing the MSE of the item parameter estimates seems inappropriate for a different reason. If the item parameter estimates are to be used for equating, for example, the appropriate quantity to minimize is the squared error in the final equating tables, not the MSE of the item parameters. If the items are to be used for subsequent adaptive testing, the appropriate criterion is a mean squared error of the resulting examinee score the adaptive test.

A thought-provoking circumstance is the following: Suppose the true prior distribution of each item parameter and ability parameter were known. Given repeated testings over a few years, we can actually come close to this. The leading Bayesian IRT practitioners prefer not to use such a 'tight' prior; they prefer to use a more diffuse prior that produces less regression of the estimates towards the mean. This attitude derives from practical considerations rather than from Bayesian logic.

Use of Bayesian priors, even diffuse priors, has several practical advantages that are widely appreciated:

1. Ability estimates ($\hat{\theta}$) on the θ scale are automatically restricted to a reasonable range. Infinite estimates do not occur.
2. Item discrimination parameter estimates never try to become infinite.
3. Estimated lower asymptotes do not come out at implausible values, even in the case of very easy items that provide no relevant data for estimating the asymptotes.

The last two advantages convince the writer that Bayesian priors should probably be used for the discrimination and the lower-asymptote parameters. Regression towards the mean in estimates of these parameters has less serious implications than in the case of the ability and difficulty parameters.

When ability parameter estimates are regressed towards the mean, an examinee's score ($\hat{\theta}$ or some transformation of $\hat{\theta}$) depends not only on the examinee's test performance, but also on the nature of the entire group in which he or she happens to be included. If the group as a whole is a low-ability group, the examinee's score may be regressed downwards; if it is a high-ability group, the examinee's score may be regressed upwards. If the group is heterogeneous, the regression effect may be small; if the group is homogeneous, the regression effect could be large. If the test is long and reliable, the regression of scores may be relatively small; if the test is short and unreliable, the regression effect could be of serious concern.

We need more practical experience in dealing with these problems in real situations. If our work deals with a single test and a single group of examinees, regressed ability estimates may pose no problem, because the rank order of the examinees' scores will be little affected. If our work deals with comparisons of individuals across groups and across tests, with data analyses made at different times, we may want more experience before we decide exactly how to obtain acceptable results for large-scale testing programs. Bayesian methods may be the ultimate recourse, but we need considerable experience with them before we can be sure how to use them safely.

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